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Procedia Computer Science 92 (2016) 396 – 403

Procedia Computer Science

2nd International Conference on Intelligent Computing, Communication & Convergence

(ICCC-2016)

Srikanta Patnaik, Editor in Chief

Conference Organized by Interscience Institute of Management and Technology

Bhubaneswar, Odisha, India

Design of MLP Based Model for Analysis of Patient Suffering from Influenza

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Abstract

Cough is a defensive system of the respiratory track that might be deliberate or reflex. It shows up with normal disease (Cold) leads towards influenza. But when it gets to be chronic it can extremely impair the life. The chronic case might lead towards tuberculosis (TB).To outline a computerized framework for influenza (Cough) detection is key aspect for medical expert and in addition to patients. The advantage could permit the evaluation of pathology in such illnesses. In this paper, authors have taken an endeavour to detect influenza in shrewd way. The model has been composed utilizing cascaded Multi-Layer Perceptron (MLP).The network is trained by LM algorithm. In initial step the symptoms are bolstered to finalize the type of pathological tests. It is encouraged with seven attributes. Once the type of pathological test has been detected, its attributes are nourished to the second stage to choose with respect to influenza or some other because of chronic case. It will help to the physicians to endorse the patients. The MLP based framework performs well as confirmed for such case.

Peer-review under responsibility of the Organizing Committee of ICCC 2016

Keywords: Multilayer Perceptron; Cascaded Network; Hidden Layer; Short Time Energy; Spectral Features

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Peer-review under responsibility of the Organizing Committee of ICCC 2016
doi:10.1016/j.procs.2016.07.396

1. Introduction

Medicinal finding is known to be subjective for several reasons and shockingly precise diagnosis of diseases has never been a simple undertaking. Actually, numerous components arrive which can muddle the determination of decision that might prompt undesirable deferral of a correct diagnosis decision. It happens so since it depends on the doctor who makes the analysis. The analyzed data helps to forecast normally. Henceforth keeping in mind the end goal to decrease the diagnosis time and enhance the diagnosis accuracy, it has turned into a need to build up the most solid and capable medical decision support systems (MDSS) with a specific end goal to bolster the undeniably muddled diagnosis decision process.

The proper representation of the above expressed certainties can be genuinely comprehended by considering "Coughing"- one of the body's defence mechanisms used to keep the passage of dust and other irritating agents into the respiratory system. It is the most widely recognized indication for which people look for medical advice as it is one of the real side effects of pneumonia and additionally asthma. In the treatment of cough related ailments, cough severity is a key component in observing the progression of disease, its counting for which its classification is an important aspect.

Cough is characterized for clinical purposes, as an expiratory move against a shut glottis, which creates a characteristic sound. It is a defensive system of the proximal respiratory tract. It might be voluntary or reflex. This symptom is the commonest explanation behind which individuals look for medical advice. It concerns one third of pulmonologist consultations. The evaluation of cough seriousness is a vital apparatus in clinical use. It requires a blend of measures portraying cough frequency, intensity and its effect on quality of life. Automatic cough screens need to face a few difficulties. A few cough monitors have been developed so far [1]. It began around the 1950s with straightforward sound recording frameworks empowering to physically detect the cough occasions. It is just as of late that (semi-or fully) automated cough recorders have been designed.

Cough is a modified respiratory act that can be initiated by two separate components, reflex cough and voluntary cough. Cough in people includes a perplexing incorporation of brainstem reflex mechanisms and voluntary cortical control [1-2]. Considers audited here focus on reflex cough by brainstem neural networks. Delineation of neural mechanisms controlling and creating reflex cough is essential for comprehension its numerous physiological and clinical complexities. Huge advancement has been made in the previous 10 years [3–7].

Computer based analysis helps the physicians for quick and easy diagnosis .In addition to it the accuracy can be increased, for development of such model; neural network plays an important role. Many researchers have taken the help of it to design the model that can help for monitoring, analysis and diagnosis. In this piece of work Multi-Layer Perceptron (MLP) neural network has been utilised by designing a cascaded neural network (CNN) for disease analysis and pathological detection for decision of diagnosis. Some of the literature has been cited in the following section related to multi-agent environment and medical diagnosis.

2. Related Literature

Vaccines for prevention of influenza in health care units are a major challenge in terms of its prevention and control. Although trivalent inactivated influenza vaccine is quite effective and safe in prevention of this disease, there is a need for further exploration for more suitable alternatives [8-9]. The need arises due to lower potential of these vaccines in case of elderly population [9-10]. Few factors that tend to make these drugs ineffective for them are age, past history of influenza exposure and chronic age related diseases [11-12]. Few of the symptoms attributed to influenza occurrence in a patient are cough, fever, weakness, stuffy nose, headache, sore throat etc. Cough is one of the crucial components related to respiratory system that can identify the progression of the diseases. Vas (Visual Analysis Scales), Cough scores and quality of life polls are few self-reported scales used to estimate the severity of this symptom [13]. Due to rough effortless impact by patient's own resilience these scales tend to be rough. Hence, cough measuring devices that can record data related to this symptom found to be more user friendly and effective [14-15]. Earlier method of deploying export to record a patient’s cough condition using audio and video monitoring devices found to be expensive [16]. Further availability of exports in a large scale poses further problem. Thus, Programed cough detection mechanism based on different pattern recognition network found their way towards modern health care systems [17]. These concepts also give insight to other symptoms of influenza. Artificial intelligence system has been successful to recognize and model biological system quite satisfactorily. The reason being, observation of different variables and symptoms related to a particular disease and severity of its constituents [15]. As these factors are based on non-linear dynamics, these can be effectively modelled by artificial neural networks [18]. ANNs have proved successful in different fields including biomedical engineering for disease diagnosis [19]. They provide non-linear relationship among hidden data describing the possible symptoms. Quick convergence, simpler algorithm, cost-effectiveness and flexibility in modelling huge dataset at ease make the network superior than other conventional modelling techniques [20]. Amongst NNs, Multilayer perceptron network (MLPN) is simplest and the standard method used for pattern recognition. Thus, this has been opted as basic building block for our cascaded network in this work. Neha *et. al.* developed Cascade correlation neural network model using both cascading framework and learning algorithm together [21]. The network found to 10 times faster than standard back-propagation algorithms. The network is reported to be effective in modelling symptoms of oral cancer and other such cases [18-20]. In these, the productive of cascaded neural network is evidenced with efficient diagnosis of coronary illness. Use of NNs effectively in similar direction has been a source of information for researchers dealing with bio-medical and health care systems [22-27]. Use of sensor such as thermistor, ECG, accelerometer, audio microphones, chest belts etc. has been used for cough symptoms leading to influenza [25]. Royal Asdi *et.al* used supervised Multi-layers Feed Forward Neural Network (SMFFNN) as a learning model for intelligent classification in [28]. They claimed the effectiveness of the system in light of potential contextual analysis, the clinical association and other such directions. Hybrid Higher Order Neural Classifier (HHONC) HHONC is presented concerning to the bosom tumour information set, Iris information set, the Glass distinguishing proof information set, the Wine acknowledgment information set, , the Balance scale information set and so on proves the relevance of NN analysis in this field [29].

In this work, mostly analysed literatures are to reflect the effectiveness of NNs in the field of medical diagnosis. The efficiently of cascaded NN proposed here may provide another successful finding in this area. This motivates to work in this area. We have designed the model to analyse the common disease of human subjects and the symptoms that lead to influenza. The preliminary detection of this disease may cure as well as check for further chronic case diagnosis. The proposed method is explained in the following section 3.

3. Proposed Method

The complete set up for detection of influenza in a patient comprises of getting patients details, dataset, data acquisition, pre-processing of data and classification scheme utilized as in Fig.1.

The information in the patient record is classified utilizing a Cascaded Neural Network (CNN) classifier. Amid training stage features of 7 attributes, for example, cough, sore throat, cerebral pain, body ache, fever, shortcoming and stuffy nose are given as input to first phase of CNN classifier to decide the danger of influenza ailment. The yield gives the required level of classification of these attributes in view of the testing features. Taking into account these classification precision a blood test or X-ray is conducted. The features in light of white blood cell (WBC), Red blood cell (RBC), blood urea, glucose level, blood platelets count obtained from the blood test is again utilized as training information as a part of second stage of the classification. These features from the properties of blood samples are utilized as training input as a part of this stage. The classification exactness is acquired for all attributes of these traits feeding utilizing features of these blood samples as testing information. In this work, 70% of data is utilized for training and 15% of data each is utilized for validation and testing individually. Along these lines, the strategy suggests a two stage classification back to back henceforth named as cascaded neural network. Based on the output a patient is identified as affliction from influenza if a specific criterion is met.

All specimens in the first stage has taking after seven features. These are cough, sore throat, headache, body ache, fever, weakness and stuffy nose. All the blood samples of second stage comprises of taking after five features: white blood cell (WBC), Red blood cess (RBC), blood urea, glucose level, blood platelets count.

The proposed framework will give a guide to the doctors to determination the disease in a more proficient manner.

The proficiency of the classifier is tested utilizing the records gathered from 150 patients. The outcomes demonstrate the CNN classifier can foresee the likelihood of patients with coronary illness (heart disease) in a more productive manner. This section depicts about the CNN classifier, its training and the role of CNN classifier for influenza disease prediction.

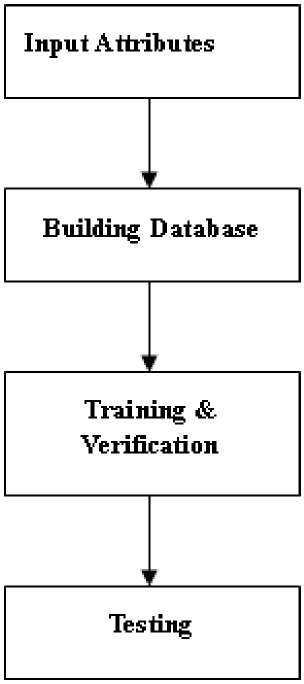

Fig. 1. Block diagram for Proposed Method

A. *Cascaded Neural Network* (CNN)

The CNN network is shown in Fig.1 below. It comprises of a cascade architecture, in which hidden neurons are added to the network each one in turn and don't change after they have been included. It is known as a cascaded in light of the fact that the output from all neurons as of now in the network bolster into new neurons. As new neurons are added to the hidden layer, the learning algorithm endeavours to augment the extent of the correlation between the new neurons output and the residual error of the network which we are trying to minimize. CNN are "self-organizing" networks. Cascade correlation network training is entirely robust, and good results more often than not can be acquired with next to zero adjustment of parameters. The network starts with only input and output neurons. Amid the training process, neurons are chosen from a pool of candidates and added to the hidden layer. CNN comprises of a layer of input units, one or more layers of hidden units, and one output layer of units. The number of input and output units relies on the application and obliges experimentation to decide the best number of hidden units.

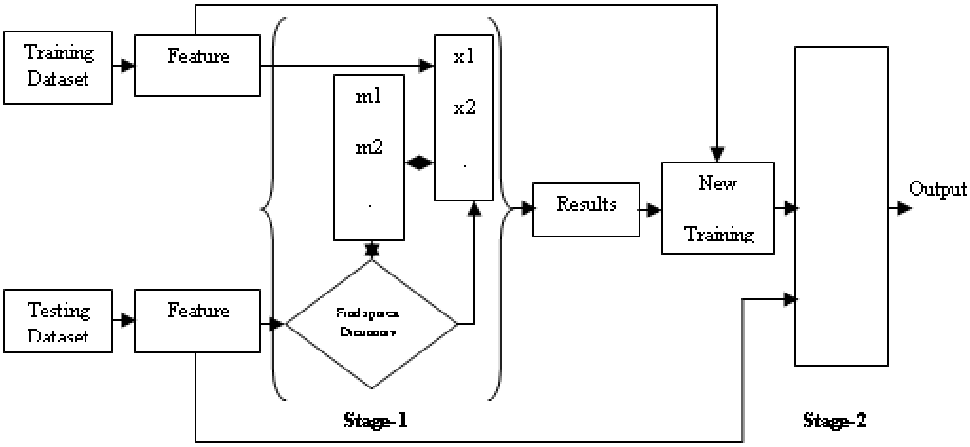

Fig.2: CNN network

A vector of predictor variable values is introduced to the input layer. Notwithstanding the predictor variables, there is a constant input of 1.0, called the bias that is fed to each of the hidden and output neurons; the bias is multiplied by a weight and added to the sum going into the neuron.

For regression, kind of issues there is just a solitary/single neuron in the output layer. Every output neuron gets values from the majority of the input neurons and the greater part of the hidden layer neurons. For classification issues, a sigmoid transfer function is utilized as the activation function. The output of first and second hidden layer utilizing m input training pattern is given respectively as

$$\vec{X}^{ij}(m) = \frac{1}{\left(1+\exp\left(W^{ij1}(m) * \vec{g}(m) + \vec{b}^{ij1}(m)\right)\right)} \tag{1}$$

$$\vec{X}^{ij2}(m) = \frac{1}{\left(1+\exp\left(W^{ij2}(m) * \vec{X}^{ij1}(m) + \vec{b}^{ij2}(m)\right)\right)} \tag{2}$$

Output of the network is given accordingly as

$$\vec{Y}^{ij2}(m) = \frac{1}{\left(1+\exp\left(W^{jk}(m) * \vec{X}^{ik2}(m) + \vec{b}^{jk}(m)\right)\right)} \tag{3}$$

Where, *Wij(m)1* is the weights, $b^{ij1}(m)$ is the biases between input and hidden layer neurons. The corresponding weights and biases between the first and second hidden layer neurons are given by $W^{ij2}(m)$ and $b^{ij2}(m)$ respectively. Similarly, $W^{jk}(m)$ signifies weights between the second hidden layer and output layer neurons with $\vec{g}(n)$ being the activation function.

Every input is connected to the output unit with the weights obtained from the Back Propagation (BP) algorithm. There is also a bias which is set to +1. Update of weights and biases take place in the network to satisfy certain error minimization criteria.

CNN Training

The training is done using back prop algorithm. Back prop uses a gradient descent method to update the weights. The algorithm used to train the dataset is discussed below,

Step 1: Initialize the input and output units based on the problem defined.

Step 2: Train the network with input and output neurons until the error no longer decreases.

Step 3: Select a temporary unit (Candidate unit) connected with the input unit and find the error.
Step 4: Train this network unit.
Step 5: Connect the temporary unit with the output unit and freeze its weights.
Step 6: Train the Input, output and the hidden unit until the error is minimized.
Step 7: Repeat the step 2 to step 6 until the net error reduction.
Neural networks can be used for prediction with various levels of success.

4. Results

The method primarily based on the information collected from precedent experiences and from current circumstances, which visualizes something as it may occur in future is known as prediction. In this work, a total of 300 data samples are used for simulating the network architecture. 210 samples are used for training and 50 samples each are used for validation and testing the system. Feature values of eight attributes of all samples have been used as input neurons and feature value of one attribute is used as output neuron in the first state of the classifier. In the second stage of the classifier the corresponding values are five and one respectively. Maximum numbers of epochs are set at 100 and the network took 72 epochs to attain the required residual error value. Initially, the signals are obtained from various attributes of the patients by several sensor mechanisms as used in multimodal framework. Several features of the patients are thus recorded and most relevant features that lead to influenza are thereby collected. Finally, these features are fed as input to the classifier for modelling the respective attributes to classify the disease accurately. Figure 3 shows the evaluation accuracy. Similarly Figure 4 and Figure 5 show the error for training and MSE respectively.

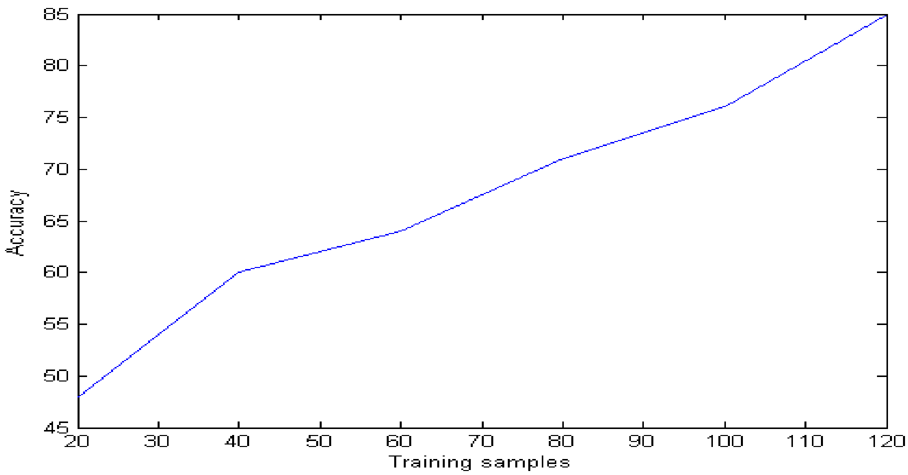

Fig. 3. Accuracy Evaluation with Training Samples

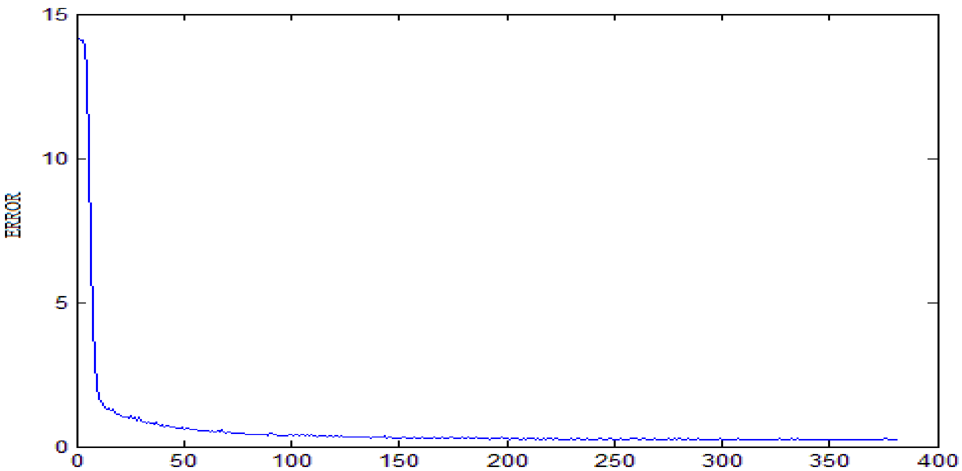

Fig. 4. Actual Testing Error after 370 epochs

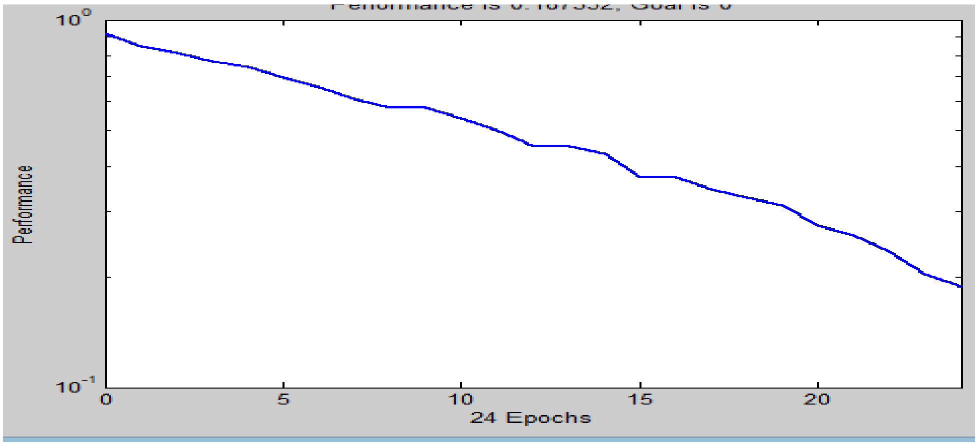

Fig.5. Mean square error performance of CNN network

5. Conclusion

In this work, an efficient model using cascaded neural network as MLP is introduced. It is trained using LM algorithm. The task for this model relates to medical diagnosis and prediction as well as the management system. Through this model was used for multi agent system and cough sound classification system, still it has the scope to use in medical diagnosis purpose further. The system is well automated and its performance is approximately up to 90%. Further it can be optimized and combined with some other classification system to enhance its performance. The system was successfully managed for the disease diagnosis.

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